

Machine Learning Discrimination Discovery and Mitigation



Background:

What is machine learning (ML) bias?

- trained model systematically generates predictions that favor advantaged group over a disadvantaged group
 - in relation to some set of attributes (e.g. race, ethnicity, gender)

Why does bias matter?

- ML is used in socially sensitive decision processes
 - hiring, loan-approval, parole-granting, etc.
- runs the risk of perpetuating socioeconomic disparities.

Goal:

How do we measure and reduce bias?

- ThemisML package
 - measures and reduces potential discrimination (PD) in ML systems.
- Assumption: Protected Class: 1 for disadvantaged group and 0 for advantaged.

Pipeline of ThemisML:

Measuring Discrimination

Measurements

- Mean difference
- Normalized mean difference

Mitigating Discrimination

Modify training process

Model Estimation

- Additive Counterfactually Fair Estimator

Preprocessing

- Relabelling

Modify training data set

Post-Processing

- Reject Option Classification

Modify predictions

Home Mortgage Dataset:

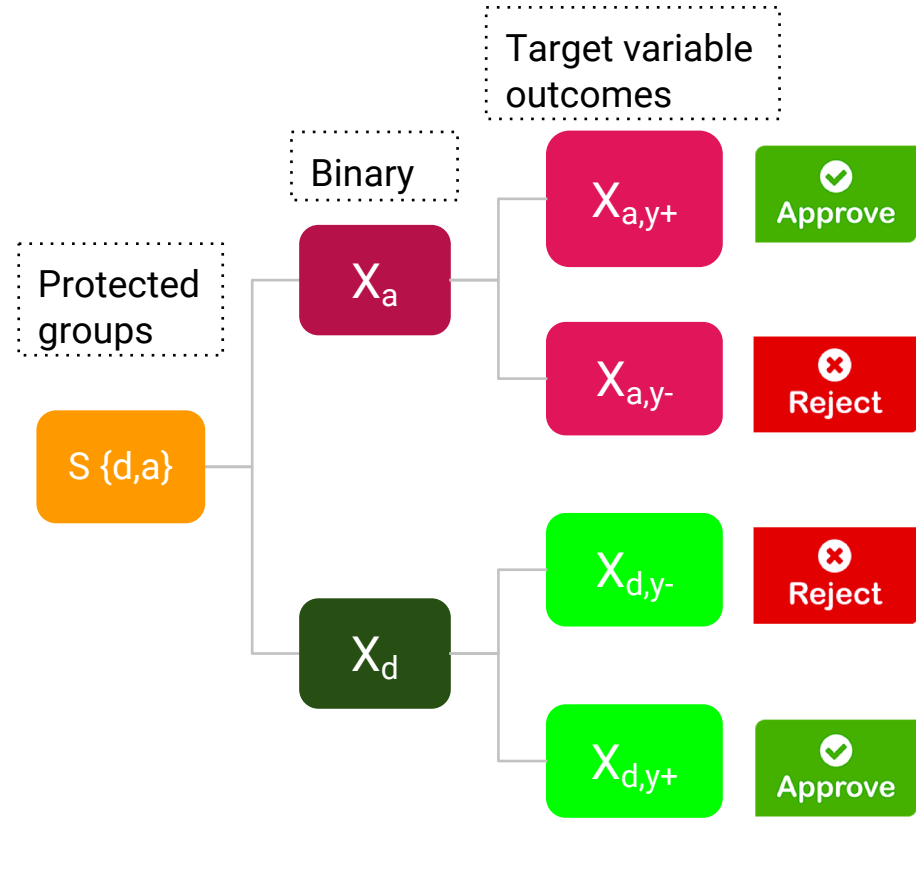
Records of loan applications include:

- **Loan information:**
 - Year, Agency, Loan Type, Amount, Decision
- **Applicant information:**
 - Gender, Race, Ethnicity, Occupancy, Income level
- **Loan validation:**
 - Result, Reason for denial

Define dependent variable Y from 'Action'

Accept?	Loan Action
1	1 -- Loan originated
1	2 -- Application approved but not accepted
0	3 -- Application denied
N/A	4 -- Application withdrawn by applicant
N/A	5 -- File closed for incompleteness
1	6 -- Loan purchased by the institution
N/A	7 -- Pre Approval request denied by financial institution
N/A	8 -- Pre Approval request approved but not accepted

Feature transformation and Metric:



-Trade-off: **Transparency** vs **Utility**

Mean difference:

Compute the mean difference in y with respect to protected class S

$$P(y+ | X_a) - P(y+ | X_d)$$

AUC

Measuring Discrimination by Features:

These mean differences (MD) and confidence interval (CI) bounds suggest that on average:

- **Men** can get a loan at a *4.6% higher rate* than **women**, with a *lower bound of 4.41%* and *upper bound of 4.78%*.
- **Non-Hispanic** people get a loan at a *5.07% higher rate* than **Hispanic** people, with a *lower bound of 4.85%* and *upper bound of 5.28%*.
- **Non-Black** people get a loan at a *8.86% higher rate* than **Black** people with a *lower bound of 8.97%* and *upper bound of 25.61%*.
- **Non-American Indian/non-Alaska Native** get a loan at *15% higher rate* than American Indian/Alaska Native with a *lower bound of 14.65%* and *upper bound of 15.36%*.

Type	Protected Class	MD (%)	MD 95% CI	Non-MD (%)	Non-MD 95% CI
Sex	Female	4.60	(4.41,4.78)	4.69	(4.50, 4.87)
Ethnicity	Hispanic	5.07	(4.85, 5.28)	5.34	(5.13, 5.55)
Race	Black	8.86	(8.03, 9.69)	10.67	(9.84, 11.50)
Race	American Indian/ Alaska Native	15.00	(14.65, 15.36)	17.45	(17.09, 17.80)

Methods

Baseline

Train model on all available variables

-Mirror the Potential Discrimination pattern in the true target variable.

- 1. Specify model hyperparameter for training models.
- 2. Partition training data into 10 validation folds (VF).
- 3. For each VF, train model on rest of VFs.
- 4. Evaluate performance of model by VF.
- 5. Choose model with best average performance.

RPA

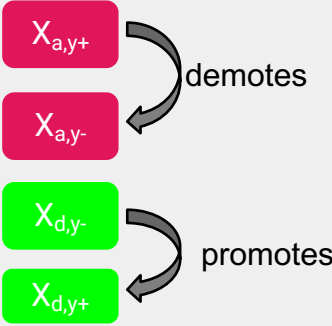
Train model on inputs without protected attributes. I.e. *Naive Fairness-Aware Model*

Protected Class
Female
Hispanic
Black
American Indian/ Alaska Native

RTV pre-possessing

Train model using the Relabelling fairness-aware method. (Reweighting; Sampling)

Generate Ranker



Then the proportion of $y+$ are equal on both X_a and X_d

ROC post-possessing

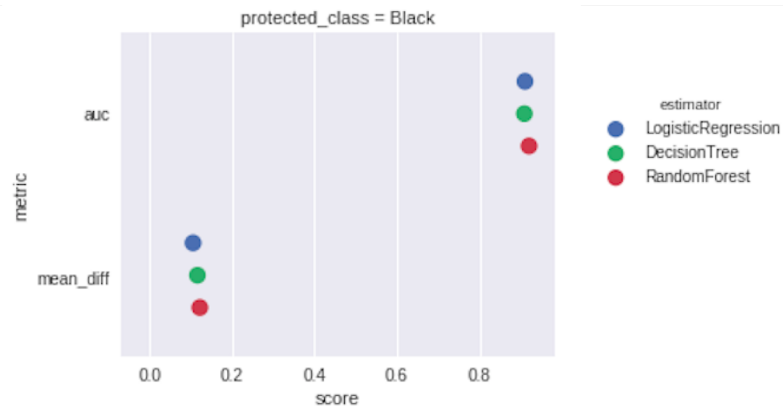
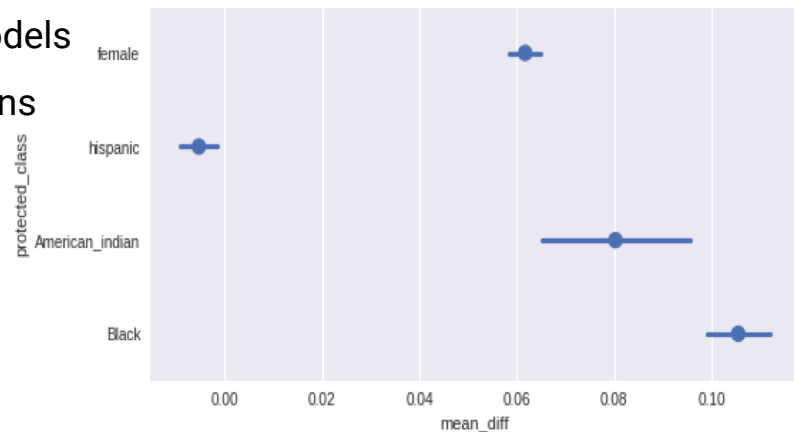
Train a model using the Reject-option classification method. (work on: Type-agnostic predictions)

- Training initial classifier **D**
Generating predicted probabilities on test set
- Computing proximity of each prediction
Get the decision boundary learned by **D**
- Assign X_d as **Y+** ; X_a as **Y-**
within the boundary (0.5~1)

Results from Baseline

- Train Logistic Regression; Decision Tree; Random forest models
- Using 10-fold-cross validation generates train/test predictions
- AUC and mean-difference metric for each condition model

			auc	mean_diff	norm_mean_diff
protected_class	estimator	fold_type			
american_indian	DecisionTree	test	0.894434	0.094912	0.118397
	LogisticRegression	test	0.902980	0.099237	0.166110
	RandomForest	test	0.914892	0.113979	0.168575
black	DecisionTree	test	0.894028	0.156533	0.225966
	LogisticRegression	test	0.902931	0.162507	0.261264
	RandomForest	test	0.915165	0.171733	0.257836
female	DecisionTree	test	0.895168	0.046437	0.051395
	LogisticRegression	test	0.902973	0.049036	0.059731
	RandomForest	test	0.915082	0.051051	0.058372
hispanic	DecisionTree	test	0.895801	0.009303	0.011770
	LogisticRegression	test	0.902929	0.002552	0.004008
	RandomForest	test	0.915168	0.013858	0.015577



Best Utility and Best Fairness

	Female		Black		American Indian		Hispanic	
	Mean-diff	AUC	Mean-diff	AUC	Mean-diff	AUC	Mean-diff	AUC
Baseline	0.046 (DT)	0.915 (RF)	0.157 (DT)	0.915 (RF)	0.095 (DT)	0.915 (RF)	0.003 (LR)	0.915 (RF)
RPA (Naive Fairness)	0.046 (LR)	0.915 (RF)	0.156 (DT)	0.915 (RF)	0.085 (LR)	0.915 (RF)	-0.002 (LR)	0.915 (RF)
RTV (Relabelling)	0.026 (DT)	0.912 (RF)	0.132 (DT)	0.911 (RF)	0.086 (LR)	0.915 (RF)	-0.001 (DT)	0.914 (RF)
Reject Option Classification	0.034 (DT)	0.925 (RF)	0.141 (DT)	0.925 (RF)	0.046 (DT)	0.925 (RF)	0.000 (DT)	0.925 (RF)

(DT: Decision Tree, RF: Random Forest, LR: Logistic Regression)

Bias amount/Tradeoff

Model Comparison (diff-of-diff)

	RTV (Relabelling)		ROC (Reject Option Classification)	
	Bias	AUC	Bias	AUC
Female	2.0 ↓	0.3 ↑	1.5 ↓	1 ↑
Black	2.5 ↓	0.4 ↑	1.5 ↓	1 ↑
A.Indian	1.1 ↓	-	5.0 ↓	1 ↑
Hispanic	0.4(-) ↓	-	0.3 ↓	1 ↑

(Unit: Percentage Point)

The Fairness-Utility Tradeoff

